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TO WHAT EXTENT DOES MENTAL HEALTH IMPACT ACADEMIC OUTCOMES? AN ANALYSIS OF PISA 2022 DATA

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ABSTRACT

This observational, retrospective study aims to find a causal relationship between mental health issues and educational outcomes in students from OECD countries, leveraging data from the Programme for International Student Assessment 2022 (PISA) by the OECD. Previous research has highlighted both the prevalence of anxiety and depression among students and the correlation between such mental health issues and poor academic outcomes. Using PISA data, this paper explores the impact of self-reported anxiety and depression on academic performance in mathematics, reading, and science. The methodology includes an Ordinary Least Squares (OLS) regression, controlling for variables such as birth month, parental education, gender, computer and internet access at home, and socioeconomic status. Results indicate that anxiety and depression can lead to worsened academic performance across all subjects, with significant p-values supporting the statistical significance of these results. These results offer evidence and reason for policymakers and educators to focus on mental health interventions to enhance student outcomes.

KEYWORDS: Mental Health, Academic Outcomes, PISA 2022 Data, Anxiety, Depression, OECD.

1. INTRODUCTION

Mental health refers to our social, psychological, and emotional well-being. As schools around the world begin investing in well-being programs and emotional-social counseling options for students, the direct impact of mental health on students' educational outcomes can be put into question. An American College Health Association study from 2022 revealed that about 35% and 27% of surveyed students have been diagnosed with anxiety and depression, respectively; 77% and 78% reported discussing anxiety or depression, respectively, with a healthcare professional in the past year (ACHA, 2024)1. This observational, retrospective study aims to understand whether mental health and educational outcomes are correlated. In an era where mental health issues such as loneliness, depression, and anxiety are prevalent in students, the findings of these studies can be used by policymakers, educators, and mental health professionals in designing educational systems to help boost student outcomes and learning abilities.

Using data from the Programme for International Student Assessment 2022 (PISA) dataset by the Organisation for Economic Cooperation and Development (OECD), this paper explores the effects of mental health issues such as anxiety and depression on the academic performance of students from OECD countries. This paper first reviews the existing literature on students' mental health and academic performance and then outlines the methodology used to derive the results. The paper then presents the results before delving into further discussions on the findings. It concludes and discusses the limitations of the research method, as well as the implications of the research.

2. Literature Review

Psychology research has been conducted that has found that mental health has negative impacts on test scores. A study by Chu et al. used 1823 Japanese undergraduate students in a longitudinal study spanning over 4-years to understand the impact of a student's mental health status (measured by the six-item Kessler Psychological Distress Scale (K6)) on their academic performance (measured through their GPA) (Chu et al., 2023). They found that the incident risk for poor academic performance was significantly greater for those in higher K6 groups, indicating more psychological distress. This research paper aims to not only verify these results but also test whether they can be generalized across OECD countries. Additionally, it tests how the impact may differ depending on the subject: math, science, or reading.

This paper aims to use the PISA dataset to do so. Firstly, the paper aims to identify a causal link between mental health and academic outcomes, especially since there are studies like Steare et al. (2023) that have identified correlational relationships between academic pressure and mental health problems. This poses a question of bidirectional ambiguity, wherein there is a possibility that negative academic outcomes can lead to academic pressure and stress that cause mental health problems, which this research aims to solve. Secondly, this paper uses an observational retrospective study design rather than an experimental design by using a pre-existing data set (PISA, 2022), which provides data on thousands of students, a far larger sample size than most studies such as Steare et al.'s (2023), which has 1823 participants, improving reliability and decreasing variability. Furthermore, the dataset measures academic performance based on 8-tests that test the ability of students to apply this knowledge and skills to non-conventional exam questions. Here, the impact of mental health can be seen on learning and the ability to apply skills rather

than solely through GPA, which, during test-anxiety, may have a significant influence and act as a confounding variable. The use of a large dataset with data on multiple variables regarding the student's background differentiates my paper as it allows for the control of variables that may not otherwise be possible.

3. METHODOLOGY

A. Data

To investigate the relationship between mental health and educational outcomes, this research uses data from the Programme for International Student Assessment 2022 (PISA) by the Organisation for Economic Cooperation and Development (OECD). PISA measures 15-year-olds' ability to apply reading, mathematics, and scientific knowledge to solve real-life challenges through a series of 8 tests. In addition to test scores, individual contextual data is also collected and used in this research, specifically data from students in OECD countries. To filter the data set for only the categories and countries needed, sort through the data, and conduct a regression analysis. I used Python code through the Jupyter Notebook software.

B. Variables

The 3 main variables of interest used in this study are test scores, anxiety, and depression. While PISA does not provide data on clinically diagnosed depression or anxiety, during the student questionnaire, students were asked to rank how often they had feelings of anxiety in the past 6 months and similarly for depression on a scale from 1-5, ranging from "rarely or never" to "almost every day." For math scores, an additional variable regarding feeling anxious about math was considered. These were used as dependent variables to understand the impact on the independent variable, their test scores, which are segregated into mathematics, reading, and science plausible values.

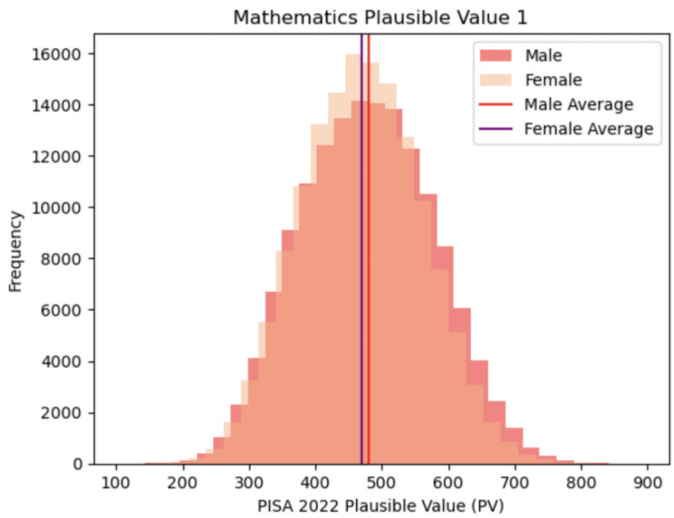
Using random assignments, students were asked to complete 1-of-8 interactive test sets, from which the test scores are represented as 10 different plausible values (PVs). A plausible value is a representation of the range of abilities that a student may have (Wu & Adams, 2022). Computing the mean of these PVs at a student level for further statistical tests could lead to bias; hence, this paper uses only PV1 from each subject.

To avoid omitted variable bias, we control for the impact of other 6 variables on test scores: birth month, parent education, gender, having a computer at home, having internet at home, and socioeconomic status. Omitting these variables would lead to an overestimation or underestimation of the effect of these variables on test scores. The sample has 295,157 students, with summary statistics shown below in *Table 1*. The count of many variables may be less than 295,157 due to missing results in the data itself.

	count	mean	std	min	25%	50%	75%	max
country	295,157.00	417.34	254.20	36.00	203.00	380.00	705.00	840.00
feel_anxious_about_math	209,139.00	2.35	1.04	1.00	1.00	2.00	3.00	4.00
feel_depressed_past_six_months	65,286.00	2.08	1.36	1.00	1.00	1.00	3.00	5.00
feel_anxious_past_six_months	65,974.00	2.36	1.46	1.00	1.00	2.00	4.00	5.00
birth_month	275,542.00	6.55	3.41	1.00	4.00	7.00	9.00	12.00
parent_education	274,621.00	14.25	2.48	3.00	12.00	16.00	16.00	16.00
gender	295,079.00	1.50	0.50	1.00	1.00	2.00	2.00	2.00
computer_at_home	278,504.00	1.07	0.26	1.00	1.00	1.00	1.00	2.00
internet_at_home	278,347.00	1.03	0.17	1.00	1.00	1.00	1.00	2.00
index_socioeconomic_status	277,632.00	0.03	0.99	-6.84	-0.62	0.16	0.82	7.38
math_score	295,157.00	474.77	95.03	105.16	406.10	473.79	541.08	892.59
science_score	295,157.00	487.44	100.88	0.00	415.58	488.06	559.01	895.38
reading_score	295,157.00	478.01	103.50	0.00	406.43	480.79	551.24	938.68

Table 1: Summary Statistics of Variables

Past research has identified relationships between each of these variables and academic performance. Birth month, for instance, is correlated with academic performance for students born earlier in the year as compared to those born later in the year (Givord, 2020) due to different ages of entry to a school or different relative ages while sitting the test at the same time. Students with lower parent education levels show poorer academic performance (Acharya & Joshi, 2009), as higher parent education levels translate to greater support for the child's performance and greater motivation, leading to better academic performance. Furthermore, access to the internet and a computer can impact scores, as computer usage involving moderate amounts of video gaming can improve visual-spatial skills (Milani et al., 2019) when combined with academic usage such as for homework, extracurricular activities, and additional reading (Simões et al., 2022). Socioeconomic status is also correlated with academic performance (Kalliganur, 2021), as students of lower socio-economic standing may have restricted access to educational resources to enhance their skills and learning. Lastly, gender has been included as a control, as within the data itself, significant differences in test outcomes between genders have been observed, as seen in Figure 1. Due to the large sample size, we can assume normality in these models.



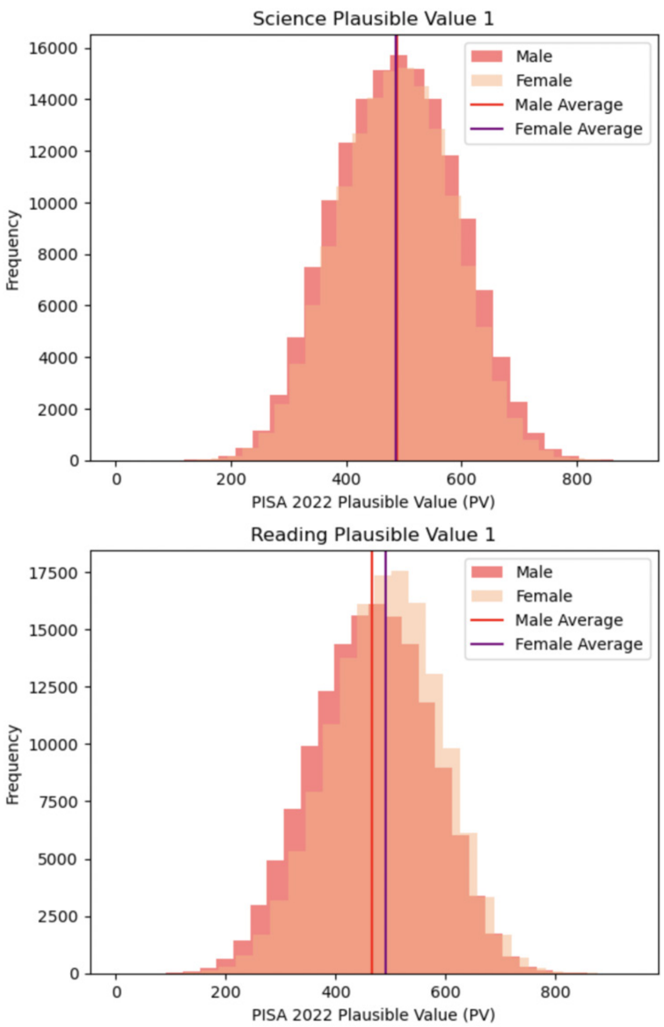


Figure 1: Normal Distribution of PV1 Test Scores for Mathematics, Reading, and Science by Gender

As seen in Figure 1, while there are gender-based gaps in test scores, they also differ depending on the subject; hence, they need to be computed separately. For mathematics, while the male average is higher than the female, the pattern is reversed for reading, where the female average is relatively higher. However, for science, the difference in means is not significant. The correlation between these different variables, especially gender, and test scores may differ depending on the subject. Hence, different predictive models for the impact of mental health on academic outcomes for the 3 subjects must be used.
Additionally, other unobserved effects from educational and institutional policies and systems set by countries may impact educational outcomes. Hence, to address these limitations, a country-fixed effects variable is introduced.

C. Model

An ordinary least-squares (OLS) regression model can be used to model the relationship between mental health and test scores. The model is an appropriate and advantageous method, as it is widely accepted for examining causal relationships. It assigns coefficients to each variable to quantify the exact impact on test scores and provides statistical tests to examine the significance of the impact of each variable on test scores.

$$S_{ci} = \mu_c + \gamma_1 D_{ci} + \gamma_2 A_{ci} + \Gamma X_{ci} + \epsilon_{ci}$$

Here, S_{ci} is the standardized test score for student i from country c, D_{ci} is the frequency of depressed feelings (ranked on a scale from 1-5), similarly, A_{ci} is the frequency of anxious feelings (ranked on a scale from 1-5), and ϵ is the error term. X_{ci} is a vector of the 6 control variables taken as mentioned above and μ_c is a vector for country-level fixed effects that is an entity-level control for governmental policies and systems regarding education that impacts all students in that country.

While this model is exactly applicable, with differing coefficient (γ) values, to both the science and reading test scores, for the math test score as the response variable, we can include another variable, $\gamma_3 AM_{ci}$, where AM_{ci} is the severity of anxious feelings about maths ranked from a scale of 1-4 for student i in country c. The OLS regression model for math scores (MS_{ci}) is seen below.

$$MS_{ci} = \mu_c + \gamma_1 D_{ci} + \gamma_2 Aci + \gamma_3 AM_{ci} + \Gamma X_{ci} + \epsilon_{ci}$$

D. Hypothesis

The null hypothesis predicts that mental health, including feelings of anxiety and depression, is not correlated with test scores. However, the alternate hypothesis for all three subjects predicts a negative impact of anxiety and a negative impact of depression on test scores. In other words, as the frequency of anxiety or depression increases, it is predicted that test scores will decrease. This hypothesis is presented mathematically below:

$$H_0: \gamma_1 = 0$$
$$H_A: \gamma_1 < 0$$

$$H_0: \gamma_2 = 0$$
$$H_A: \gamma_2 < 0$$

For math in particular, I expect a positive relationship between anxiety regarding math variables and test scores. While I do predict that as anxiety regarding math increases, test scores will decrease, the scoring for this question during data collection from 1-4 describes a value of 1 as strongly agreeing to feelings of anxiety regarding math, while 4 refers to "strongly disagree." Hence, it is predicted that a higher number from 1-4 positively correlates with an increase in test scores. Here H_0M is the null hypothesis and H_AM is the alternate hypothesis, both specific to math scores.

$$H_{0M}: \gamma_3 = 0$$
$$H_{AM}: \gamma_3 > 0$$

4. RESULTS & DISCUSSION

A. Regression Table

OLS Regression Results

Dep. Variable:	math_score	R-squared:	0.257
Model:	OLS	Adj. R-squared:	0.256
Method:	Least Squares	F-statistic:	714.8
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	0.00
Time:	20:25:02	Log-Likelihood:	-2.6212e+05
No. Observations:	45583	AIC:	5.243e+05
Df Residuals:	45560	BIC:	5.245e+05
Df Model:	22		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.296e+12	3.78e+12	1.401	0.161	-2.11e+12	1.27e+13
C(feel_anxious_about_math)[T.2.0]	-1.4225	0.944	-1.506	0.132	-3.274	0.429
C(feel_anxious_about_math)[T.3.0]	10.3113	1.041	9.906	0.000	8.271	12.352
C(feel_anxious_about_math)[T.4.0]	32.8499	1.196	27.468	0.000	30.506	35.194
C(feel_depressed_past_six_months)[T.2.0]	2.3632	1.007	2.347	0.019	0.390	4.336
C(feel_depressed_past_six_months)[T.3.0]	-4.5535	1.295	-3.517	0.000	-7.091	-2.016
C(feel_depressed_past_six_months)[T.4.0]	-2.8345	1.402	-2.022	0.043	-5.583	-0.086
C(feel_depressed_past_six_months)[T.5.0]	-11.7387	1.571	-7.473	0.000	-14.818	-8.660
C(feel_anxious_past_six_months)[T.2.0]	10.2585	1.029	9.967	0.000	8.241	12.276
C(feel_anxious_past_six_months)[T.3.0]	5.0554	1.241	4.072	0.000	2.622	7.489
C(feel_anxious_past_six_months)[T.4.0]	6.1447	1.388	4.426	0.000	3.424	8.866
C(feel_anxious_past_six_months)[T.5.0]	-1.6271	1.485	-1.096	0.273	-4.538	1.283
C(computer_at_home)[T.2.0]	-14.3595	1.616	-8.884	0.000	-17.527	-11.192
C(internet_at_home)[T.2.0]	-7.8163	2.667	-2.931	0.003	-13.044	-2.589
C(gender)[T.2.0]	9.5276	0.761	12.518	0.000	8.036	11.019
parents_education	-6.5685	0.232	-28.358	0.000	-7.022	-6.114
index_socioeconomic_status	43.5547	0.639	68.159	0.000	42.302	44.807

Figure 2: Regression Results for Mathematics Score

OLS Regression Results

Dep. Variable:	science_score	R-squared:	0.203
Model:	OLS	Adj. R-squared:	0.203
Method:	Least Squares	F-statistic:	785.5
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	0.00
Time:	21:37:17	Log-Likelihood:	-3.4300e+05
No. Observations:	58562	AIC:	6.860e+05
Df Residuals:	58542	BIC:	6.862e+05
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.862e+11	8.19e+11	0.227	0.820	-1.42e+12	1.79e+12
C(feel_depressed_past_six_months)[T.2.0]	2.2408	0.983	2.280	0.023	0.314	4.167
C(feel_depressed_past_six_months)[T.3.0]	-2.7448	1.255	-2.187	0.029	-5.205	-0.285
C(feel_depressed_past_six_months)[T.4.0]	-2.3362	1.360	-1.717	0.086	-5.003	0.330
C(feel_depressed_past_six_months)[T.5.0]	-7.1927	1.518	-4.737	0.000	-10.169	-4.216
C(feel_anxious_past_six_months)[T.2.0]	9.1736	0.999	9.178	0.000	7.215	11.133
C(feel_anxious_past_six_months)[T.3.0]	5.1921	1.190	4.362	0.000	2.859	7.525
C(feel_anxious_past_six_months)[T.4.0]	6.3126	1.324	4.769	0.000	3.718	8.907
C(feel_anxious_past_six_months)[T.5.0]	1.1877	1.414	0.840	0.401	-1.584	3.959
C(computer_at_home)[T.2.0]	-15.6102	1.574	-9.918	0.000	-18.695	-12.525
C(internet_at_home)[T.2.0]	-6.6439	2.476	-2.683	0.007	-11.498	-1.790
C(gender)[T.2.0]	7.2807	0.740	9.836	0.000	5.830	8.732
parents_education	-6.4226	0.225	-28.591	0.000	-6.863	-5.982
index_socioeconomic_status	44.2133	0.623	70.994	0.000	42.993	45.434

Figure 3: Regression Results for Science Score

OLS Regression Results

Dep. Variable:	reading_score	R-squared:	0.198
Model:	OLS	Adj. R-squared:	0.198
Method:	Least Squares	F-statistic:	762.3
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	0.00
Time:	21:37:34	Log-Likelihood:	-3.4490e+05
No. Observations:	58562	AIC:	6.898e+05
Df Residuals:	58542	BIC:	6.900e+05
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.29e+10	8.46e+11	0.015	0.988	-1.65e+12	1.67e+12
C(feel_depressed_past_six_months)[T.2.0]	6.1371	1.015	6.045	0.000	4.147	8.127
C(feel_depressed_past_six_months)[T.3.0]	-5.0763	1.297	-3.915	0.000	-7.618	-2.535
C(feel_depressed_past_six_months)[T.4.0]	3.8828	1.405	2.763	0.006	1.128	6.637
C(feel_depressed_past_six_months)[T.5.0]	-6.3878	1.569	-4.072	0.000	-9.462	-3.313
C(feel_anxious_past_six_months)[T.2.0]	13.3466	1.032	12.927	0.000	11.323	15.370
C(feel_anxious_past_six_months)[T.3.0]	11.2221	1.230	9.127	0.000	8.812	13.632
C(feel_anxious_past_six_months)[T.4.0]	14.2854	1.367	10.447	0.000	11.605	16.966
C(feel_anxious_past_six_months)[T.5.0]	6.2286	1.461	4.264	0.000	3.366	9.092
C(computer_at_home)[T.2.0]	-19.4481	1.626	-11.962	0.000	-22.635	-16.261
C(internet_at_home)[T.2.0]	-14.1846	2.558	-5.545	0.000	-19.199	-9.171
C(gender)[T.2.0]	-20.2491	0.765	-26.482	0.000	-21.748	-18.750
parents_education	-6.2021	0.232	-26.728	0.000	-6.657	-5.747
index_socioeconomic_status	42.6948	0.643	66.366	0.000	41.434	43.956

Figure 4: Regression Results for Reading Score

*(**Note:** The country-fixed effects and the complete regression table can be found in the appendix.)*

As observed in *Figure 1*, *Figure 2*, and *Figure 3* above, the impact of mental health on standardised test scores follows a similar pattern for each subject. For all 3 - math, science, and reading - the coefficient of the anxiety variable decreases as the input value (2, 3, 4, or 5) increases. While the coefficient does not necessarily always follow the hypothesised negative value (H_A:γ_2<0), the decreasing coefficient indicates a negative correlation between anxiety and test scores. More specifically, this can be interpreted as a student who feels anxious more than once a week (ranked 4) as compared to a student who feels anxious about every day (ranked 5) is expected to score 7.7718, 5.1249, and 8.0568 points higher, considering all other variables in the model are held constant. The p-values of the anxiety variables almost all lie in a significant region at a 99.9% confidence level since the p>|t| is equal to 0.00, apart from 2 outliers where the values are 0.273 (maths level 5 anxiety score) and 0.401 (science level 5 anxiety score), indicating that the impact of feelings of anxiety on test scores is statistically significant in all subject areas. The clear pattern of decreasing coefficient values, often going from positive to negative as the anxiety score increases from 1 to 4, indicates that an increased frequency of anxiety has adverse impacts on academic performance and test scores. Thus, the null hypothesis is rejected and the alternate hypothesis is accepted.

Furthermore, anxiety solely about math has a very similar impact on test scores that adhere to the initial hypothesis. A student who strongly disagrees with the claim that they feel anxious about math compared to someone who agrees is estimated to score 34.2724 points higher on average. This indicates that an increase in anxiety about math contributes to lower math test scores. However, while the impact of disagreeing or strongly disagreeing is statistically significant, the impact of agreeing has a p-value of 0.132, indicating that even at a 95% or 90% confidence level, the impact of this is not as significant.

Similarly, the same pattern is seen across all subjects for the variable of depression that is scored and measured the same way. The coefficient of the depression variable mostly decreases as the frequency of depression measured from 1-5 increases. In context, this means that a student who feels depressed about every month (ranked 2) as compared to about every day (ranked 5) is on average estimated to score 14.1019, 9.4335, and 12.5249 higher in math, science, and reading, respectively. Hence, similar to the impact of anxiety, an increased frequency of depression negatively impacts academic performance and test scores.

Unfortunately, the R-squared values of each model range from 0.198 to 0.257, depending on the subject, indicating that only between 19.8% and 25.7% of the variability in the response model is explained by the regression model. While this is very low, in social science research where there is an inherent amount of unexplained variability, an R-squared value of 0.1 (10%) is acceptable under the condition that the explanatory variables are statistically significant (Ozili & Peterson, 2023). Since we are not trying to predict scores based on these variables but rather just observe whether there is a significant causal relationship between mental health and test scores, this low R-squared value is justified. However, adding additional control variables has aided in increasing the amount of explained variability since the impact of having a computer or internet at home, the child's parent's education or socio-economic status, and gender are all statistically significant at the 99% confidence level.

The findings about gender and test scores support existing

research as the impact of being a male is estimated to decrease reading test scores by 20.2491 points, indicating the gender-based gap as women score higher (Smith & Reimer, 2023). However, for math and science, males have a statistically significant advantage and score 9.5276 and 7.2807 points, respectively, higher than women, supporting general trends in research (Reilly, Neumann, & Andrews, 2014). Additionally, by accounting for country-level fixed effects, we can generalize these findings across students (15-year-olds) in OECD countries.

B. Limitations

The research, despite being able to find a meaningful causal relationship between mental health and test scores, has some limitations that must be noted and considered while applying results and evaluating the reliability of the model.

Firstly, despite having a large sample size of 195,157 students, due to missing responses in multiple questions, the final regression model relies on only between 45,000 and 58,000 students' responses (depending on each subject's regression model), which is roughly 23.05% to 27.92% of the total sample. A smaller sample size increases variability and decreases statistical power as they have a higher chance of being influenced by random variations, making it harder to detect true effects. Additionally, common to most research, the dataset uses a sample survey rather than a census to collect data; hence, only a sample of the entire population's data is analyzed through this research. This makes it more difficult to generalize the sample to the entire population, for which a census would be more representative of the entire population.

Secondly, social science concepts such as anxiety and depression can be difficult to operationalize. The PISA dataset attempts to do so by measuring its frequency on a scale of 1-5, where 1 is "Never or Almost Never", while 5 is "All or Almost All The Time". However, each student's interpretation of these values may differ. Additionally, the variable fails to measure the severity of the problem, for example, a student with slight anxiety all the time may be in a completely different situation than someone with clinically diagnosed severe anxiety all the time. However, the variable measures both the same way, as it only considers frequency. Moreover, as the data tests feelings of anxiety and depression rather than the clinical diagnosis of these disorders, in many participants' cases, feelings of nervousness and sadness may be reported as anxiety and depression, respectively, which is inaccurate. This raises difficulties with the accurate operationalization of the independent variable in this research.

Thirdly, the use of an online survey as the data collection method can introduce several limitations. For example, participants may be subject to social desirability bias as they may underreport these feelings of anxiety to be perceived as strong; however, the maintenance of anonymity through the survey aids in decreasing the impact of this bias. Additionally, due to gender differences associated with traditional gender roles, men often experience more externalizing symptoms (i.e., violence, substance abuse) than internally accepting their feelings (Smith, Mouzon, & Elliot, 2016). In a survey where these tests of mental health are based on self-reported symptoms, men may underreport their struggles. Furthermore, due to the lengthy nature of the test, participants may not think through each response to each question and instead may hastily respond, leading to possible biases and less reliable data.

Lastly, despite using control variables to decrease omitted variable bias, there are still many other variables impacting test scores that are not accounted for. For example, despite using a country variable that may control for macro-based education policies and structures, the individual school-level impacts are not controlled for. Each school, as a sub-unit level of the country variable, may have differing teaching quality, funding, syllabus and curriculum, day lengths, and start dates, all of which may impact outcomes. Additionally, the causes of their mental health issues may impact their test scores differently. For example, mental health issues due to academic pressures may influence a student's test scores and academic performance differently than someone with anxiety or depression due to social or personal pressures apart from academics.

5. CONCLUSION

This research paper provides a comprehensive analysis of the relationship between mental health and academic performance, which can be generalized to students in OECD countries as it uses PISA 2022 data. With the use of ordinary least squares (OLS) regression, we have statistically significant evidence that a higher frequency of self-reported depression and anxiety leads to worsened academic performance in mathematics, reading, and science, allowing us to reject the null hypothesis. While not the focus of the study, the research even underlines significant gender-based gaps in academic outcomes, which support existing trends: females tend to score higher in reading, whereas males score significantly higher in math and science.

The research highlights the importance of addressing mental health issues within educational contexts as schools and policymakers understand the detrimental effects of anxiety and depression on students' learning abilities and academic outcomes. Implementing well-being programs and professional social-emotional counseling teams is just one of the ways to help mitigate these effects and support a child's academic success.

However, the study does acknowledge some of its limitations, including potential biases in the data itself and from unaccounted-for variables that may influence test scores. Despite these limitations, the study does offer valuable and reliable insights as it takes advantage of a huge sample size and takes into account other extraneous variables that are often not considered or collected in many experimental studies.

6. APPENDIX

OLS Regression Results

Dep. Variable:	math_score	R-squared:	0.257
Model:	OLS	Adj. R-squared:	0.256
Method:	Least Squares	F-statistic:	714.8
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	0.00
Time:	20:25:02	Log-Likelihood:	-2.6212e+05
No. Observations:	45583	AIC:	5.243e+05
Df Residuals:	45560	BIC:	5.245e+05
Df Model:	22		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	5.296e+12	3.78e+12	1.401	0.161	-2.11e+12	1.27e+13
C(feel_anxious_about_math)[T.2.0]	-1.4225	0.944	-1.506	0.132	-3.274	0.429
C(feel_anxious_about_math)[T.3.0]	10.3113	1.041	9.906	0.000	8.271	12.352
C(feel_anxious_about_math)[T.4.0]	32.8499	1.196	27.468	0.000	30.506	35.194
C(feel_depressed_past_six_months)[T.2.0]	2.3632	1.007	2.347	0.019	0.390	4.336
C(feel_depressed_past_six_months)[T.3.0]	-4.5535	1.295	-3.517	0.000	-7.091	-2.016
C(feel_depressed_past_six_months)[T.4.0]	-2.8345	1.402	-2.022	0.043	-5.583	-0.086
C(feel_depressed_past_six_months)[T.5.0]	-11.7387	1.571	-7.473	0.000	-14.818	-8.660
C(feel_anxious_past_six_months)[T.2.0]	10.2585	1.029	9.967	0.000	8.241	12.276
C(feel_anxious_past_six_months)[T.3.0]	5.0554	1.241	4.072	0.000	2.622	7.489
C(feel_anxious_past_six_months)[T.4.0]	6.1447	1.388	4.426	0.000	3.424	8.866
C(feel_anxious_past_six_months)[T.5.0]	-1.6271	1.485	-1.096	0.273	-4.538	1.283
C(computer_at_home)[T.2.0]	-14.3595	1.616	-8.884	0.000	-17.527	-11.192
C(internet_at_home)[T.2.0]	-7.8163	2.667	-2.931	0.003	-13.044	-2.589
C(gender)[T.2.0]	9.5276	0.761	12.518	0.000	8.036	11.019
C(country)[T.40.0]	-3.248e-06	2.32e-06	-1.401	0.161	-7.79e-06	1.3e-06
C(country)[T.56.0]	-8.607e-17	1.32e-16	-0.650	0.516	-3.46e-16	1.74e-16
C(country)[T.124.0]	1.441e-16	1.69e-16	0.854	0.393	-1.87e-16	4.75e-16
C(country)[T.152.0]	-2.43e-15	2.27e-16	-10.696	0.000	-2.88e-15	-1.98e-15
C(country)[T.170.0]	-1.795e-15	2.86e-16	-6.278	0.000	-2.36e-15	-1.23e-15
C(country)[T.188.0]	1.11e-15	8.78e-17	12.642	0.000	9.38e-16	1.28e-15
C(country)[T.203.0]	3.208e-16	3.67e-17	8.741	0.000	2.49e-16	3.93e-16
C(country)[T.208.0]	2.565e-16	7.67e-17	3.346	0.001	1.06e-16	4.07e-16
C(country)[T.233.0]	0	0	nan	nan	0	0
C(country)[T.246.0]	0	0	nan	nan	0	0
C(country)[T.250.0]	0	0	nan	nan	0	0
C(country)[T.276.0]	0	0	nan	nan	0	0
C(country)[T.300.0]	0	0	nan	nan	0	0
C(country)[T.348.0]	-5.296e+12	3.78e+12	-1.401	0.161	-1.27e+13	2.11e+12
C(country)[T.352.0]	0	0	nan	nan	0	0
C(country)[T.372.0]	-5.296e+12	3.78e+12	-1.401	0.161	-1.27e+13	2.11e+12
C(country)[T.376.0]	0	0	nan	nan	0	0
C(country)[T.380.0]	0	0	nan	nan	0	0
C(country)[T.392.0]	0	0	nan	nan	0	0
C(country)[T.410.0]	0	0	nan	nan	0	0
C(country)[T.428.0]	0	0	nan	nan	0	0
C(country)[T.440.0]	0	0	nan	nan	0	0
C(country)[T.484.0]	-5.296e+12	3.78e+12	-1.401	0.161	-1.27e+13	2.11e+12
C(country)[T.528.0]	-5.296e+12	3.78e+12	-1.401	0.161	-1.27e+13	2.11e+12
C(country)[T.554.0]	-5.296e+12	3.78e+12	-1.401	0.161	-1.27e+13	2.11e+12
C(country)[T.578.0]	0	0	nan	nan	0	0
C(country)[T.616.0]	0	0	nan	nan	0	0
C(country)[T.620.0]	0	0	nan	nan	0	0
C(country)[T.703.0]	0	0	nan	nan	0	0
C(country)[T.705.0]	-5.296e+12	3.78e+12	-1.401	0.161	-1.27e+13	2.11e+12
C(country)[T.724.0]	-5.296e+12	3.78e+12	-1.401	0.161	-1.27e+13	2.11e+12
C(country)[T.752.0]	0	0	nan	nan	0	0
C(country)[T.756.0]	0	0	nan	nan	0	0
C(country)[T.792.0]	0	0	nan	nan	0	0
C(country)[T.826.0]	0	0	nan	nan	0	0
C(country)[T.840.0]	0	0	nan	nan	0	0
parents_education	-6.5685	0.232	-28.358	0.000	-7.022	-6.114
index_socioeconomic_status	43.5547	0.639	68.159	0.000	42.302	44.807

Figure 5: Regression Results for Mathematics Score

OLS Regression Results

Dep. Variable:	science_score	R-squared:	0.203
Model:	OLS	Adj. R-squared:	0.203
Method:	Least Squares	F-statistic:	785.5
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	0.00
Time:	21:37:17	Log-Likelihood:	-3.4300e+05
No. Observations:	58562	AIC:	6.860e+05
Df Residuals:	58542	BIC:	6.862e+05
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.862e+11	8.19e+11	0.227	0.820	-1.42e+12	1.79e+12
C(feel_depressed_past_six_months)[T.2.0]	2.2408	0.983	2.280	0.023	0.314	4.167
C(feel_depressed_past_six_months)[T.3.0]	-2.7448	1.255	-2.187	0.029	-5.205	-0.285
C(feel_depressed_past_six_months)[T.4.0]	-2.3362	1.360	-1.717	0.086	-5.003	0.330
C(feel_depressed_past_six_months)[T.5.0]	-7.1927	1.518	-4.737	0.000	-10.169	-4.216
C(feel_anxious_past_six_months)[T.2.0]	9.1736	0.999	9.178	0.000	7.215	11.133
C(feel_anxious_past_six_months)[T.3.0]	5.1921	1.190	4.362	0.000	2.859	7.525
C(feel_anxious_past_six_months)[T.4.0]	6.3126	1.324	4.769	0.000	3.718	8.907
C(feel_anxious_past_six_months)[T.5.0]	1.1877	1.414	0.840	0.401	-1.584	3.959
C(computer_at_home)[T.2.0]	-15.6102	1.574	-9.918	0.000	-18.695	-12.525
C(internet_at_home)[T.2.0]	-6.6439	2.476	-2.683	0.007	-11.498	-1.790
C(gender)[T.2.0]	7.2807	0.740	9.836	0.000	5.830	8.732
C(country)[T.40.0]	-1.695e-15	2.2e-16	-7.718	0.000	-2.13e-15	-1.26e-15
C(country)[T.56.0]	1.547e-15	1.42e-16	10.909	0.000	1.27e-15	1.82e-15
C(country)[T.124.0]	2.855e-08	1.26e-07	0.227	0.820	-2.18e-07	2.75e-07
C(country)[T.152.0]	-6.343e-16	7.89e-17	-8.042	0.000	-7.89e-16	-4.8e-16
C(country)[T.170.0]	-5.029e-18	3.47e-17	-0.145	0.885	-7.31e-17	6.31e-17
C(country)[T.188.0]	1.211e-15	1.23e-16	9.823	0.000	9.69e-16	1.45e-15
C(country)[T.203.0]	2.54e-16	6.27e-17	4.054	0.000	1.31e-16	3.77e-16
C(country)[T.208.0]	2.54e-16	6.27e-17	4.054	0.000	1.31e-16	3.77e-16
C(country)[T.233.0]	0	0	nan	nan	0	0
C(country)[T.246.0]	0	0	nan	nan	0	0
C(country)[T.250.0]	0	0	nan	nan	0	0
C(country)[T.276.0]	0	0	nan	nan	0	0
C(country)[T.300.0]	0	0	nan	nan	0	0
C(country)[T.348.0]	-1.862e+11	8.19e+11	-0.227	0.820	-1.79e+12	1.42e+12
C(country)[T.352.0]	0	0	nan	nan	0	0
C(country)[T.372.0]	-1.862e+11	8.19e+11	-0.227	0.820	-1.79e+12	1.42e+12
C(country)[T.376.0]	0	0	nan	nan	0	0
C(country)[T.380.0]	0	0	nan	nan	0	0
C(country)[T.392.0]	0	0	nan	nan	0	0
C(country)[T.410.0]	0	0	nan	nan	0	0
C(country)[T.428.0]	0	0	nan	nan	0	0
C(country)[T.440.0]	0	0	nan	nan	0	0
C(country)[T.484.0]	-1.862e+11	8.19e+11	-0.227	0.820	-1.79e+12	1.42e+12
C(country)[T.528.0]	-1.862e+11	8.19e+11	-0.227	0.820	-1.79e+12	1.42e+12
C(country)[T.554.0]	-1.862e+11	8.19e+11	-0.227	0.820	-1.79e+12	1.42e+12
C(country)[T.578.0]	0	0	nan	nan	0	0
C(country)[T.616.0]	0	0	nan	nan	0	0
C(country)[T.620.0]	0	0	nan	nan	0	0
C(country)[T.703.0]	0	0	nan	nan	0	0
C(country)[T.705.0]	-1.862e+11	8.19e+11	-0.227	0.820	-1.79e+12	1.42e+12
C(country)[T.724.0]	-1.862e+11	8.19e+11	-0.227	0.820	-1.79e+12	1.42e+12
C(country)[T.752.0]	0	0	nan	nan	0	0
C(country)[T.756.0]	0	0	nan	nan	0	0
C(country)[T.792.0]	0	0	nan	nan	0	0
C(country)[T.826.0]	0	0	nan	nan	0	0
C(country)[T.840.0]	0	0	nan	nan	0	0
parents_education	-6.4226	0.225	-28.591	0.000	-6.863	-5.982
index_socioeconomic_status	44.2133	0.623	70.994	0.000	42.993	45.434

Figure 6: Regression Results for Science Score

OLS Regression Results

Dep. Variable:	reading_score	R-squared:	0.198
Model:	OLS	Adj. R-squared:	0.198
Method:	Least Squares	F-statistic:	762.3
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	0.00
Time:	21:37:34	Log-Likelihood:	-3.4490e+05
No. Observations:	58562	AIC:	6.898e+05
Df Residuals:	58542	BIC:	6.900e+05
Df Model:	19		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.29e+10	8.46e+11	0.015	0.988	-1.65e+12	1.67e+12
C(feel_depressed_past_six_months)[T.2.0]	6.1371	1.015	6.045	0.000	4.147	8.127
C(feel_depressed_past_six_months)[T.3.0]	-5.0763	1.297	-3.915	0.000	-7.618	-2.535
C(feel_depressed_past_six_months)[T.4.0]	3.8828	1.405	2.763	0.006	1.128	6.637
C(feel_depressed_past_six_months)[T.5.0]	-6.3878	1.569	-4.072	0.000	-9.462	-3.313
C(feel_anxious_past_six_months)[T.2.0]	13.3466	1.032	12.927	0.000	11.323	15.370
C(feel_anxious_past_six_months)[T.3.0]	11.2221	1.230	9.127	0.000	8.812	13.632
C(feel_anxious_past_six_months)[T.4.0]	14.2854	1.367	10.447	0.000	11.605	16.966
C(feel_anxious_past_six_months)[T.5.0]	6.2286	1.461	4.264	0.000	3.366	9.092
C(computer_at_home)[T.2.0]	-19.4481	1.626	-11.962	0.000	-22.635	-16.261
C(internet_at_home)[T.2.0]	-14.1846	2.558	-5.545	0.000	-19.199	-9.171
C(gender)[T.2.0]	-20.2491	0.765	-26.482	0.000	-21.748	-18.750
C(country)[T.40.0]	-8.683e-16	2.27e-16	-3.828	0.000	-1.31e-15	-4.24e-16
C(country)[T.56.0]	2.011e-15	1.46e-16	13.729	0.000	1.72e-15	2.3e-15
C(country)[T.124.0]	1.979e-09	1.3e-07	0.015	0.988	-2.52e-07	2.56e-07
C(country)[T.152.0]	-1.041e-15	8.15e-17	-12.772	0.000	-1.2e-15	-8.81e-16
C(country)[T.170.0]	5.317e-16	3.59e-17	14.817	0.000	4.61e-16	6.02e-16
C(country)[T.188.0]	2.49e-15	1.27e-16	19.557	0.000	2.24e-15	2.74e-15
C(country)[T.203.0]	5.653e-17	6.47e-17	0.873	0.383	-7.04e-17	1.83e-16
C(country)[T.208.0]	5.653e-17	6.47e-17	0.873	0.383	-7.04e-17	1.83e-16
C(country)[T.233.0]	0	0	nan	nan	0	0
C(country)[T.246.0]	0	0	nan	nan	0	0
C(country)[T.250.0]	0	0	nan	nan	0	0
C(country)[T.276.0]	0	0	nan	nan	0	0
C(country)[T.300.0]	0	0	nan	nan	0	0
C(country)[T.348.0]	-1.29e+10	8.46e+11	-0.015	0.988	-1.67e+12	1.65e+12
C(country)[T.352.0]	0	0	nan	nan	0	0
C(country)[T.372.0]	-1.29e+10	8.46e+11	-0.015	0.988	-1.67e+12	1.65e+12
C(country)[T.376.0]	0	0	nan	nan	0	0
C(country)[T.380.0]	0	0	nan	nan	0	0
C(country)[T.392.0]	0	0	nan	nan	0	0
C(country)[T.410.0]	0	0	nan	nan	0	0
C(country)[T.428.0]	0	0	nan	nan	0	0
C(country)[T.440.0]	0	0	nan	nan	0	0
C(country)[T.484.0]	-1.29e+10	8.46e+11	-0.015	0.988	-1.67e+12	1.65e+12
C(country)[T.528.0]	-1.29e+10	8.46e+11	-0.015	0.988	-1.67e+12	1.65e+12
C(country)[T.554.0]	-1.29e+10	8.46e+11	-0.015	0.988	-1.67e+12	1.65e+12
C(country)[T.578.0]	0	0	nan	nan	0	0
C(country)[T.616.0]	0	0	nan	nan	0	0
C(country)[T.620.0]	0	0	nan	nan	0	0
C(country)[T.703.0]	0	0	nan	nan	0	0
C(country)[T.705.0]	-1.29e+10	8.46e+11	-0.015	0.988	-1.67e+12	1.65e+12
C(country)[T.724.0]	-1.29e+10	8.46e+11	-0.015	0.988	-1.67e+12	1.65e+12
C(country)[T.752.0]	0	0	nan	nan	0	0
C(country)[T.756.0]	0	0	nan	nan	0	0
C(country)[T.792.0]	0	0	nan	nan	0	0
C(country)[T.826.0]	0	0	nan	nan	0	0
C(country)[T.840.0]	0	0	nan	nan	0	0
parents_education	-6.2021	0.232	-26.728	0.000	-6.657	-5.747
index_socioeconomic_status	42.6948	0.643	66.366	0.000	41.434	43.956

Figure 7: Regression Results for Reading Score

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